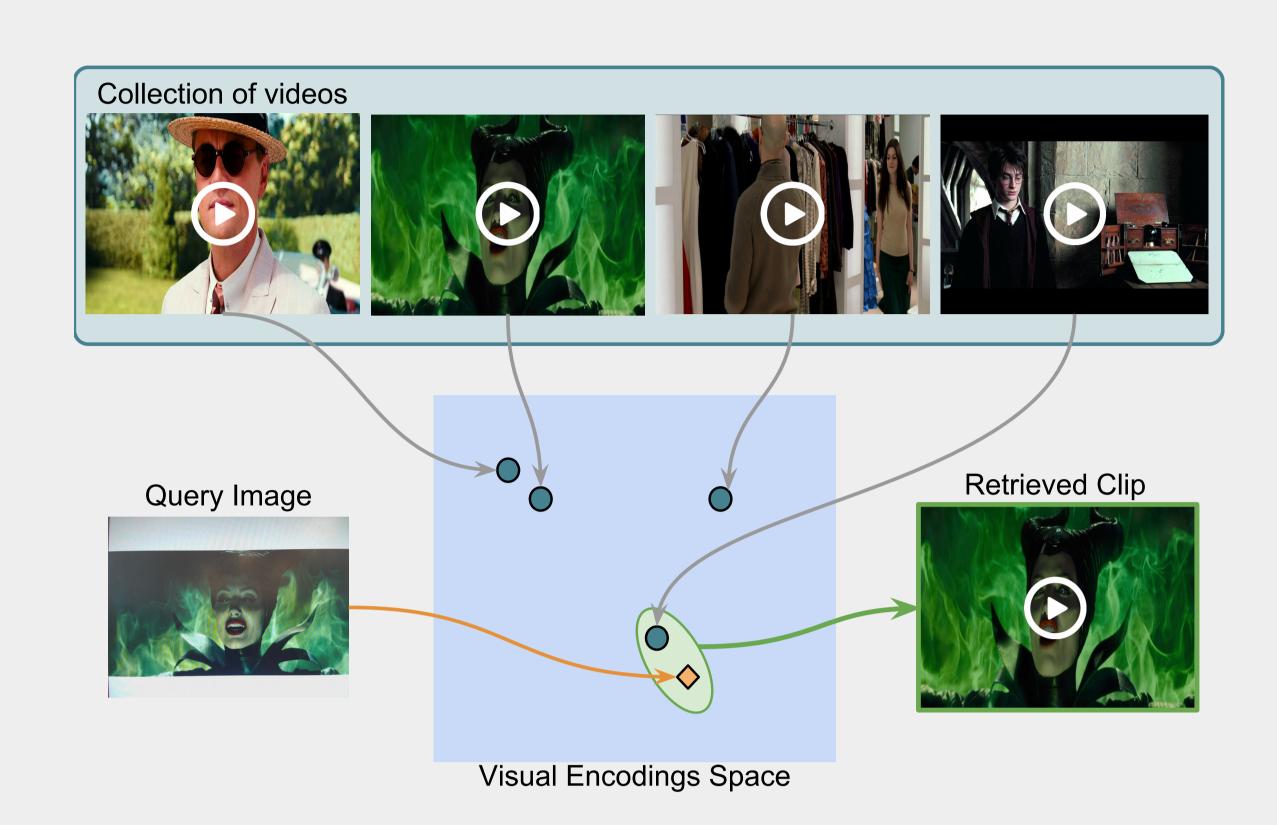
# **Asymmetric Spatio-Temporal Embeddings** for Large-Scale Image-to-Video Retrieval

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#### INTRODUCTION



# Image-to-Video Retrieval

Finding video clips in a large-scale collections using static images.

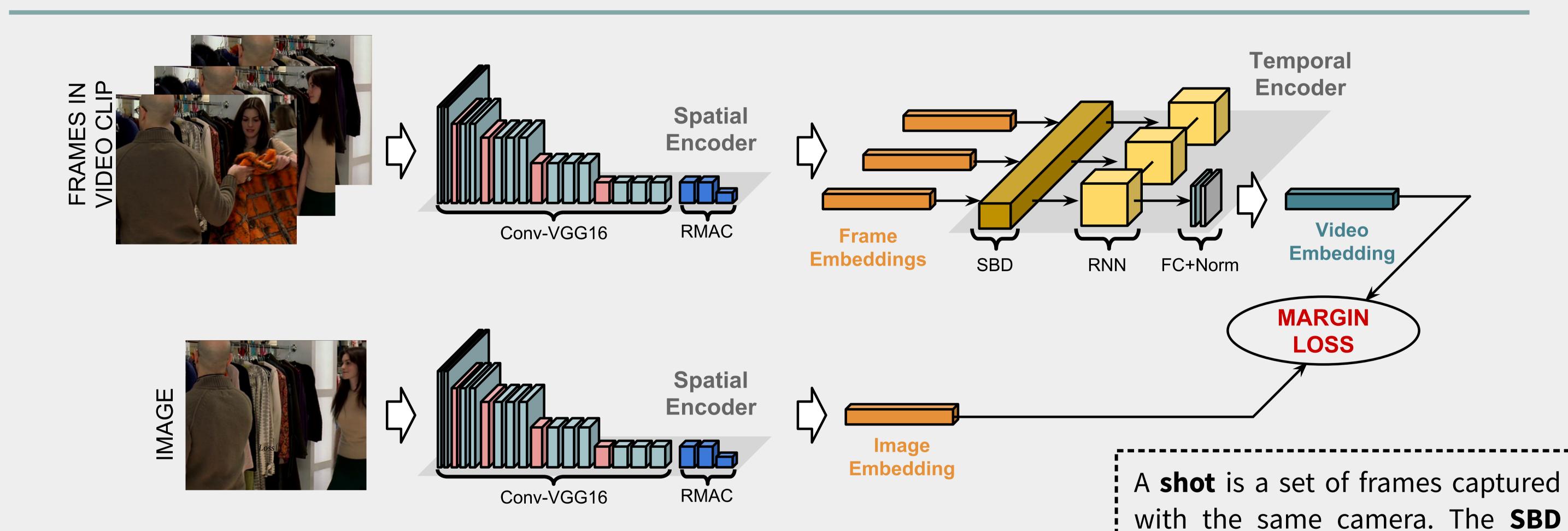
## Challenges

- Asymmetry: different processing tools for images and videos.
- Scalability: the number of frames scales very fast.
- Efficiency: to reduce the amount of data to be processed.

### We propose

To encode images and videos into a common embedding space using an asymmetric spatio-temporal encoder.

### MODEL

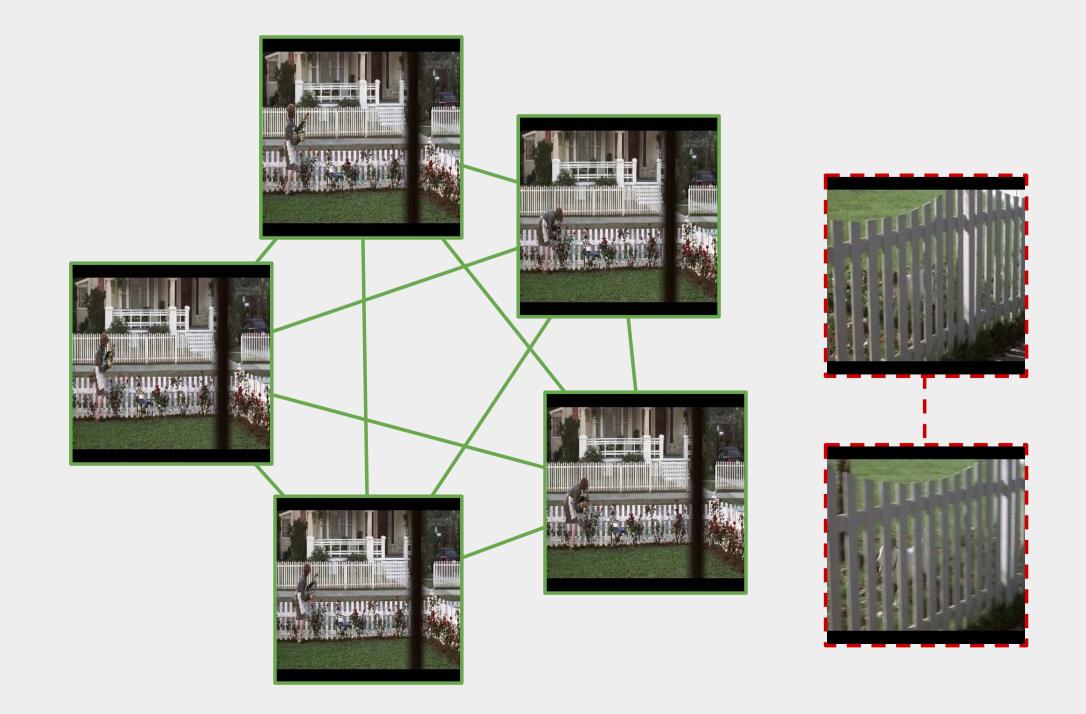


$$Loss(F_i, \vartheta_i) = y_i(1 - cos(F_i, \vartheta_i)) + (1 - y_i)(max(0, cos(F_i, \vartheta_i) - \Delta))$$

We use pairs of {frame, video} for training and we ensure that the distar matching pairs (y = 1) is less than the distance between non-matching

# **Training Data**

- LSMDC (Rohrbach et al., 2017) with 40 movies and 26,496 clips.
- Shots obtained from clips using data graphs.



ethod	dim SI2V [5] VB [6]
ESULTS	
	0.2 - 0.0 -
nce between pairs (y = 0).	Distance 0.4 -
$,\vartheta_i)-\Delta))$	0.8 - Shot 1 Shot 2 Shot 3 Shot 4

detects shot boundaries when the

Distance between consecutive frames

distance between frames is large.

Method	dim	<b>SI2V</b> [5]	<b>VB</b> [6]
Scene FV [3]	65,536	0.500	0.622
Sum-Pool Alexnet FC6 [3]	4,096	0.071	0.012
Sum-Pool AlexNet FC7 [3]	4,096	0.065	0.013
Sum-Pool VGG16 FC6 [3]	4,096	0.067	0.013
Sum-Pool VGG16 FC7 [3]	4,096	0.069	0.011
Ours (LSTM)	<b>512</b>	0.602	0.580
Ours (GRU)	<b>512</b>	0.606	0.572